Robust Control 2000

Lecture 7

- RS and H_{∞} Optimization of Coprime Factors.
- H_{∞} Loop Shaping Procedure.
- Justification of H_{∞} Loop Shaping.

State Space Formulas

Consider a state space representation of the strictly proper plant

$$P = \left(\begin{array}{c|c} A & B \\ \hline C & 0 \end{array}\right).$$

It is easy to verify that

$$[\tilde{N} \ \tilde{M}] = \left(\begin{array}{c|c} A + LC & B & L \\ \hline C & 0 & I \end{array} \right),$$

where A + LC is stable, gives a left coprime factorization. Then

$$G = \begin{pmatrix} A & -L & B \\ \hline \begin{pmatrix} 0 \\ C \end{pmatrix} & \begin{pmatrix} 0 \\ I \end{pmatrix} & \begin{pmatrix} I \\ 0 \\ C \end{pmatrix} \\ C & I & 0 \end{pmatrix}$$

Note: $D_{11} \neq 0$. Hence

$$\frac{1}{\epsilon_{opt}} = \gamma_{opt} > \|I\| = 1 \quad \Leftrightarrow \quad \epsilon_{opt} < 1.$$

Robust Stabilization of Coprime Factors

Left coprime factor uncertainty model:

$$P_{\Delta} = (ilde{M} + ilde{\Delta}_M)^{-1} (ilde{N} + ilde{\Delta}_N).$$

By Small Gain Theorem:

RS for $\|[\tilde{\Delta}_N \ \Delta_M]\|_{\infty} \leq \epsilon$ iff

$$\left\| \begin{pmatrix} K \\ I \end{pmatrix} (I + PK)^{-1} \tilde{M}^{-1} \right\|_{\infty} < \frac{1}{\epsilon}.$$

This is H_{∞} optimization.

In the standard lower LFT form

$$\begin{pmatrix} K\\I \end{pmatrix} (I+PK)^{-1}\tilde{M}^{-1} = \mathcal{F}_l(G,K)$$

where

$$G = \begin{pmatrix} 0 & I \\ \underline{\tilde{M}^{-1}} & -P \\ \hline \underline{\tilde{M}^{-1}} & -P \end{pmatrix}.$$

H_{∞} optimization of Coprime Factors

Apply H_{∞} optimization result to G ([Zhou,Th. 14.7]). Two Hamiltonian matrices are

$$H_{\infty} = \begin{pmatrix} A - \frac{1}{\gamma^{2} - 1}LC & \frac{1}{\gamma^{2} - 1}LL^{*} - BB^{*} \\ -\frac{\gamma^{2}}{\gamma^{2} - 1}C^{*}C & -(A - \frac{1}{\gamma^{2} - 1}LC)^{*} \end{pmatrix},$$
$$J_{\infty} = \begin{pmatrix} (A + LC)^{*} & -C^{*}C \\ 0 & -(A + LC) \end{pmatrix}.$$

Note that $Y_{\infty} = 0$. Thus the result becomes

Theorem: Let D = 0. Then there exists a stabilizing controller *K* such that

$$\|\mathcal{F}_l(G,K)\|_{\infty} < \gamma$$

 $\begin{array}{l} \text{if and only if } \gamma > 1, \, H_\infty \in \, \operatorname{dom}(\operatorname{Ric}) \text{ and} \\ X_\infty = \operatorname{Ric}(H_\infty) \geq 0. \end{array}$

Remark: The result depends on the choice of *L*, i.e. choice of coprime factors.

Normalized Coprime Factors

Let choose *L* such that \tilde{M} and \tilde{N} become the normalized left coprime factors.

Let *Y* be the stabilizing solution to

$$AY + YA^* - YC^*CY + BB^* = 0.$$

The matrix $A - YC^*C$ is stable, so we can put

 $L=-YC^*.$

Lemma: With the choice $L = -YC^*$ the left coprime factors become normalized.

Proof: Denote $\mathcal{A}(s) = (sI - A + YC^*C)^{-1}$ and calculate

$$\begin{pmatrix} \tilde{N} & \tilde{M} \end{pmatrix} \begin{pmatrix} N^* \\ \tilde{M}^* \end{pmatrix} = I - C\mathcal{A}YC^* - CY\mathcal{A}^*C^* + + C\mathcal{A}(B^*B + YC^*CY)\mathcal{A}^*C^* = = I + C\mathcal{A}(B^*B + YC^*CY - Y(\mathcal{A}^*)^{-1} - \mathcal{A}^{-1}Y)\mathcal{A}^*C^* = = I + C\mathcal{A}(\underline{B^*B - YC^*CY + AY + YA^*})\mathcal{A}^*C^* = I. = 0$$

Proof: Denote

$$\begin{split} H_q &= \left(\begin{array}{cc} A - YC^*C & 0 \\ -C^*C & -(A - YC^*C)^* \end{array} \right) \,, \\ T &= \left(\begin{array}{cc} I & -\frac{\gamma^2}{\gamma^2 - 1}Y \\ 0 & \frac{\gamma^2}{\gamma^2 - 1}I \end{array} \right) \,. \end{split}$$

It is straightforward to see that

 $H_{\infty} = TH_qT^{-1}.$

Since $Q = \operatorname{Ric}(H_q)$ we have the stable invariant subspace for H_∞ as

$$T \left(egin{array}{c} I \ Q \end{array}
ight) \, = \, \left(egin{array}{c} I - rac{\gamma^2}{\gamma^2 - 1} Y Q \ rac{\gamma^2}{\gamma^2 - 1} Q \end{array}
ight) \, .$$

Finally $\exists X_{\infty} \geq 0$ iff

$$I - rac{\gamma^2}{\gamma^2 - 1} YQ > 0 \quad \Leftrightarrow \quad \gamma^2 > rac{1}{1 - \lambda_{max}(YQ)}.$$

Note that *Y* and *Q* are controllability and observability Gramians for $[\tilde{N} \ \tilde{M}]$. Hence $\lambda_{max}(YQ)$ is the square of the Hankel norm of it.

H_{∞} Optimization of Normalized Coprime Factors

Theorem: Let D = 0 and $L = -YC^*$ where $Y \ge 0$ is the stabilizing solution to

 $AY + YA^* - YC^*CY + BB^* = 0.$

Then $P = \tilde{M}^{-1}\tilde{N}$ is a normalized left coprime factorization and

$$\inf_{K-\text{stab}} \left\| \begin{pmatrix} K \\ I \end{pmatrix} (I+PK)^{-1} \tilde{M}^{-1} \right\|_{\infty} =$$

$$= \frac{1}{\sqrt{1-\lambda_{max}(YQ)}} = \left(1 - \|\tilde{N} \ \tilde{M}\|_{H}^{2}\right)^{-1/2} = \gamma_{opt}$$

where

$$Q(A - YC^*C) + (A - YC^*C)^*Q + C^*C = 0.$$

Moreover, a controller achieving $\gamma > \gamma_{opt}$ is

$$\begin{split} K(s) &= \left(\begin{array}{c|c} A - BB^*X_{\infty} - YC^*C & -YC^* \\ \hline -B^*X_{\infty} & 0 \end{array} \right), \\ X_{\infty} &= \frac{\gamma^2}{\gamma^2 - 1}Q\left(I - \frac{\gamma^2}{\gamma^2 - 1}YQ\right)^{-1}. \end{split}$$

Some related H_∞ problem

Since \tilde{M} , \tilde{N} are the normalized lcf we have

$$\left(\begin{array}{cc} \tilde{M} & \tilde{N} \end{array} \right) \left(\begin{array}{cc} \tilde{M} & \tilde{N} \end{array} \right)^* = I.$$

Therefore

$$\left\| \begin{pmatrix} K \\ I \end{pmatrix} (I + PK)^{-1} \tilde{M}^{-1} \right\| =$$

$$= \left\| \begin{pmatrix} K \\ I \end{pmatrix} (I + PK)^{-1} \tilde{M}^{-1} \begin{pmatrix} \tilde{M} & \tilde{N} \end{pmatrix} \right\| =$$

$$= \left\| \begin{pmatrix} K \\ I \end{pmatrix} (I + PK)^{-1} \begin{pmatrix} I & P \end{pmatrix} \right\|.$$

Does not depend on factorization.

Corollary:

$$\inf_{K-\text{stab}} \left\| \begin{pmatrix} K \\ I \end{pmatrix} (I+PK)^{-1} \begin{pmatrix} I & P \end{pmatrix} \right\|_{\infty} = \\ = \frac{1}{\sqrt{1-\lambda_{max}(YQ)}} = (1-\|\tilde{N} \ \tilde{M}\|_{H}^{2})^{-1/2} = \gamma_{opt}.$$

Right Coprime Factors

What if we have normalized rcf $P = NM^{-1}$?

Theorem:

$$\left\| \begin{pmatrix} I \\ K \end{pmatrix} (I + PK)^{-1} \begin{pmatrix} I & P \end{pmatrix} \right\| =$$
$$= \left\| \begin{pmatrix} I \\ P \end{pmatrix} (I + KP)^{-1} \begin{pmatrix} I & K \end{pmatrix} \right\|$$

Corollary: Let $P = NM^{-1} = \tilde{M}^{-1}\tilde{N}$ be the normalized rcf and lcf, respectively. Then

$$\left\| \begin{pmatrix} K \\ I \end{pmatrix} (I + PK)^{-1} \tilde{M}^{-1} \right\|_{\infty} =$$

= $\left\| M^{-1} (I + KP)^{-1} \begin{pmatrix} I & K \end{pmatrix} \right\|_{\infty}.$

<u>Conclusion</u>: It does not matter what kind of factorization we have. One can work with either.

Relation to Gain and Phase Margins

Theorem: Let P be a SISO plant and K be a stabilizing controller. Then

gain margin $\geq \frac{1+b_{P,K}}{1-b_{P,K}}$, phase margin $\geq 2 \arcsin(b_{P,K})$.

Proof: For SISO system at every ω

$$b_{P,K} = \frac{1}{\|\dots\|_{\infty}} \le \frac{1}{\|\dots\|} = \frac{|1+P(j\omega)K(j\omega)|}{\left\|\begin{pmatrix}1\\K\end{pmatrix}\left(1-P\right)\right\|} =$$
$$= \frac{|1+P(j\omega)K(j\omega)|}{\left\|\begin{pmatrix}1\\K\end{pmatrix}\right\|\left\|\left(1-P\right)\right\|} =$$
$$= \frac{|1+P(j\omega)K(j\omega)|}{\sqrt{1+|P(j\omega)|^2}\sqrt{1+|K(j\omega)|^2}}.$$

Stability Margin

Introduce a quantity $b_{P,K}$

$$b_{P,K} = \begin{cases} \left(\left\| \begin{pmatrix} I \\ K \end{pmatrix} (I + PK)^{-1} \begin{pmatrix} I & P \end{pmatrix} \right\|_{\infty} \right)^{-1} \\ \text{if } K \text{ stabilizes } P, \\ 0 \quad \text{otherwise} \end{cases}$$

and

$$b_{opt} = \sup b_{P,K}.$$

Then $b_{P,K} = b_{K,P}$ and

$$b_{opt} = \sqrt{1 - \lambda_{max}(YQ)} = \sqrt{1 - \|\tilde{N} \ ilde{M}\|_{H}^2}.$$

It holds $0 \leq b_{opt} \leq 1$. The larger b_{opt} the more robustly stable the closed loop system.

This quantity is related to the classical gain and phase margins. Thus it can be considered as a general stability margin (Vinnicombe, 1993).

So at frequencies where $k:=-PK\in R^+$ we have

$$\begin{array}{rcl} b_{P,K} & \leq & \displaystyle \frac{|1-k|}{\sqrt{(1+|P|^2)(1+k^2/|P|^2)}} \leq \\ & \leq & \displaystyle \frac{|1-k|}{\sqrt{\min_P\{(1+|P|^2)(1+k^2/|P|^2)\}}} = \displaystyle \frac{|1-k|}{|1+k|} \end{array}$$

from which the gain margin result follows.

Similarly at frequencies where $PK = -e^{\theta}$

$$\begin{array}{rcl} b_{P,K} & \leq & \frac{|1-e^{\theta}|}{\sqrt{(1+|P|^2)(1+1/|P|^2)}} \leq \\ & \leq & \frac{|1-e^{\theta}|}{\sqrt{\min_P\{(1+|P|^2)(1+1/|P|^2)\}}} = \\ & = & \frac{2|\sin(\theta/2)|}{2} \end{array}$$

which implies the phase margin result.



$$\left\| \begin{pmatrix} I \\ K_{\infty} \end{pmatrix} (I + P_s K_{\infty})^{-1} \tilde{M}_s^{-1} \right\|_{\infty} =$$

$$= \left\| \begin{pmatrix} W_2 \\ W_1^{-1} K \end{pmatrix} (I + PK)^{-1} \begin{pmatrix} W_2^{-1} & PW_1 \end{pmatrix} \right\|_{\infty}$$

So it has an interpretation of the standard H_{∞} optimization problem with weights.

• BUT!!! The open loop under investigation on Step 2 is $W_2PW_1K_{\infty}$ and $K_{\infty}W_2PW_1$ whereas the actual open loop is given by $W_1K_{\infty}W_2P$ and $PW_1K_{\infty}W_2$. This is not really what we has shaped!

Thus the method needs validation.

 $\underline{\sigma}(KP) = \underline{\sigma}(W_1 K_{\infty} P_s W_1^{-1}) \geq \frac{\underline{\sigma}(P_s) \underline{\sigma}(K_{\infty})}{\kappa(W_1)}$

where κ denotes conditional number.

Thus small $\underline{\sigma}(K_{\infty})$ might cause problem even if P_s is large. Can this happen?

Theorem: Any K_{∞} such that $b_{P_{s},K_{\infty}} \geq 1/\gamma$ also satisfies

$$\underline{\sigma}(K_{\infty}) \geq \frac{\underline{\sigma}(P_s) - \sqrt{\gamma^2 - 1}}{\sqrt{\gamma^2 - 1}\underline{\sigma}(P_s) + 1} \quad \text{if } \underline{\sigma}(P_s) > \sqrt{\gamma^2 - 1}.$$

Corollary: If $\underline{\sigma}(P_s) >> \sqrt{\gamma^2 - 1}$ then

$$\underline{\sigma}(K_{\infty}) \geq rac{1}{\sqrt{\gamma^2-1}}.$$

Consider now high frequency region.

$$\overline{\sigma}(PK) = \overline{\sigma}(W_2^{-1}P_sK_{\infty}W_2) \le \overline{\sigma}(P_s)\overline{\sigma}(K_{\infty})\kappa(W_2), \ \overline{\sigma}(KP) = \overline{\sigma}(W_1K_{\infty}P_sW_1^{-1}) \le \overline{\sigma}(P_s)\overline{\sigma}(K_{\infty})\kappa(W_1).$$

Can $\overline{\sigma}(K_{\infty})$ be large if $\overline{\sigma}(P_s)$ is small?

Theorem: Any K_{∞} such that $b_{P_s,K_{\infty}} \geq 1/\gamma$ also satisfies

$$\overline{\sigma}(K_{\infty}) \leq \frac{\sqrt{\gamma^2 - 1} + \overline{\sigma}(P_s)}{1 - \sqrt{\gamma^2 - 1}\overline{\sigma}(P_s)} \quad \text{if } \overline{\sigma}(P_s) < \frac{1}{\sqrt{\gamma^2}}$$

Corollary: If $\overline{\sigma}(P_s) << 1/\sqrt{\gamma^2-1}$ then

$$\overline{\sigma}(K_{\infty}) \leq \sqrt{\gamma^2 - 1}.$$

One can get the idea of proof from SISO relation

$$b_{P,K} \leq rac{|1+P_s(j\omega)K_\infty(j\omega)|}{\sqrt{1+|P_s(j\omega)|^2}\sqrt{1+|K_\infty(j\omega)|^2}}.$$

What have we learned today?

- H_{∞} optimization of normalized coprime factors. Optimal value can be calculated via Hankel norm of the factors.
- Left or right coprime factors does not matter.
- Stability margin *b*_{*P,K*}. The larger the better. Relation to gain and phase margins.
- H_{∞} loop shaping via pre- and postcompensations and optimization of $b_{P,K}$.
- Relations PK, $KP \leftrightarrow P_s$, W.

Denote

$$\overline{\sigma}_i = \overline{\sigma}(W_i), \quad \underline{\sigma}_i = \underline{\sigma}(W_i), \quad \kappa_i = \kappa(W_i).$$

Theorem: Let *P* be the nominal plant and let $K = W_1 K_{\infty} W_2$ be the controller designed by loop shaping. Then if $b_{P_s,K_{\infty}} \ge 1/\gamma$ then

$$\overline{\sigma}(K(I+PK)^{-1}) \leq \gamma \overline{\sigma}(\tilde{M}_s)\overline{\sigma}_1\overline{\sigma}_2, \\ \overline{\sigma}((I+PK)^{-1}) \leq \min\{\gamma \overline{\sigma}(\tilde{M}_s)\kappa_2, 1+\gamma \overline{\sigma}(\tilde{N}_s)\kappa_2\}, \\ K(I+PK)^{-1}P) \leq \min\{\gamma \overline{\sigma}(\tilde{N}_s)\kappa_1, 1+\gamma \overline{\sigma}(\tilde{M}_s)\kappa_1\}, \\ \overline{\sigma}((I+PK)^{-1}P) \leq \frac{\gamma \overline{\sigma}(\tilde{N}_s)}{\underline{\sigma}_1\underline{\sigma}_2}, \\ \overline{\sigma}((I+KP)^{-1}) \leq \min\{1+\gamma \overline{\sigma}(\tilde{N}_s)\kappa_1, \gamma \overline{\sigma}(\tilde{M}_s)\kappa_1\}, \\ \overline{\sigma}(P(I+KP)^{-1}K) \leq \min\{1+\gamma \overline{\sigma}(\tilde{M}_s)\kappa_2, \gamma \overline{\sigma}(\tilde{N}_s)\kappa_2\}$$

where

$$egin{array}{rcl} \overline{\sigma}(ilde{N}_s) &=& \overline{\sigma}(N_s) = \left(rac{\overline{\sigma}^2(P_s)}{1+\overline{\sigma}^2(P_s)}
ight)^{1/2}, \ \overline{\sigma}(ilde{M}_s) &=& \overline{\sigma}(M_s) = \left(rac{1}{1+\overline{\sigma}^2(P_s)}
ight)^{1/2}. \end{array}$$

Next lecture

- Gap Metric and *v*-Gap Metric.
- Extended Loop Shaping.